# An Adaptive Fuzzy Current Controller With Neural Network for a Field-Oriented Controller Induction Machine

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**ABSTRACT**

*Recently, the development of novel control methodology enabled us to improve the performance of AC-machine drives by using pulse width modulation (PWM) technique. Usually, the dynamic characteristic of induction motor (IM) has been represented by the fifth order nonlinear differential equation. This dynamics, however, can be reduced to third order dynamics by applying direct control of IM input current. This methodology concludes that it is much easier to control IM by means of the field-oriented methods using the current controller. Therefore a precise current control is crucial to achieve a high control performance both in dynamic and steady-state operations.*

*This paper presents an adaptive fuzzy current controller with artificial neural network (ANN) for field-oriented controlled IM. This new control structure is able to adaptively minimize a current ripple while maintaining constant switching frequency. The proposed controller especially uses neuro-computing philosophy as well as adaptive learning pattern recognizing principles with respect to variations of the system parameters. The proposed approach is applied to the IM drive system, and its performance is tested through various simulations. Simulation results show that the proposed system, compared among several known classical methods, has a superb performance.*

KEYWORDS: ***Induction motor, inverter, field-oriented control, current control, fuzzy control, neural network, estimation unit***

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Received November 11, 1992; accepted August 15, 1993.

International Journal of Approximate Reasoning 1994; 10:45–61

655 Avenue of the Americas, New York, NY 10010 0888-613X/94/$7.00

## 1. INTRODUCTION

The field-oriented control approach to the application of induction motor (IM) drive system has achieved high control performance, which could be available through only DC motor drive system. The dynamic characteristic of IM has been represented by the fifth order nonlinear differential equation. This dynamic, however, can be reduced to third order dynamics by applying direct control of IM input current [1]. Therefore, precise current control is crucial for high control performance.

Recently, fuzzy theory and artificial neural network technology has been applied to the motor current control system [2]. For instance, application of artificial neural network (ANN) to IM current control system is proposed by Song et al. [3], where a neural network generates optimal switching pattern and control pulse width modulation (PWM) signals directly while being continuously trained to update a certain knowledge represented by the specific characteristic features of IM drive system. This system, however, should use the off-line learning method with respect to the specific pattern of IM drive system at initial control stage. This is because ANN could not sufficiently learn the characteristics of IM at initial stage, by which the control system can neither control nor learn simultaneously. This prompts us to develop fuzzy current controller [4], which is able to achieve the control objective from the initial state. The fuzzy current controller has the following advantages: (1) it does not require modeling and analysis of IM, (2) it is applicable to the nonlinear system, and (3) it can exploit experts' knowledge. Even though it has several advantages over conventional controllers, there still remains the unresolved problem of the general methodology for choosing an optimal scaling factor and designing proper membership function.

As a conventional control approach, the hysteresis current controlled voltage source inverter (CC-VSI) was proposed by Plunkett [5]. This approach has been rapidly spread out in AC motor drive systems, because it can reduce the order of system dynamics as mentioned previously. From CC-VSI, many control schemes have also been developed [6]. The control goal of CC-VSI is first to achieve the high control performance, second to reduce losses due to the harmonic from load side by minimizing the current ripple, and third to reduce the switching losses of power component device. Hysteresis current controllers use some type of hysteresis in the comparison of the line currents to the current references. A current controller with hysteresis band [7] has a simple control structure and has the capability to limit peak current in which, however, the switching frequency to enforce current within the hysteresis band cannot be maintained constant; it is varied in accordance with load and speed variation.

This incurs excessive harmonics. In order to achieve a constant switching frequency, the ramp comparison controller [8] has been proposed. The ramp comparison controller compares the current errors to a triangle waveform to generate the inverter firing signals. This method, however, generates a possible phase delay that deteriorates the system performance. In addition, if the motor time constant is smaller than the slope of the ramp wave, multiple modulation would be generated in the one period of reference ramp signal. Predictive controllers calculate the inverter voltages required to force the currents to follow the current reference. Two types of predictive current controllers on the basis of space vector have been developed: one put emphasis on the constant switching frequency [9], and the other on the minimum switching frequency [10]. Both types of predictive current controllers require an excessive computation time to obtain the next switching state.

This paper extends the previous fuzzy current controller [4] to a novel adaptive fuzzy current controller by combining ANN technology principle [11]. The proposed approach in this study is able to not only improve the control performance but also resolve the problems remained in the current controller for the field-oriented IM drive system. Moreover, the proposed current controller is able to reduce the current ripple adaptively while maintaining a constant switching frequency even under the parameter variation and abrupt load changes.

## 2. PROPOSED CURRENT CONTROLLER

In general, the requirements for the high performance current control system are: (1) fast tracking performance, (2) minimum current ripple, (3) robustness to parameter variation, and (4) zero steady-state error in both reference tracking and load regulation. This paper uses fuzzy control approach in order to achieve a robust control structure to the parameter variation. This is because the fuzzy current controller does not require the exact dynamics of IM to be controlled. Hence, the performance of the fuzzy controller might be more insensitive to the parameter variation than conventional controllers based on exact mathematical model [12]. There is, however, no concrete design methodology for fuzzy rule-based control algorithm. In many cases, there is difficulty in tuning parameters used in fuzzy controller (i.e., scale factor, shape of membership function, etc.). Moreover, when the variation of motor parameters occurs, the current error is no longer minimized, therefore, it is required for additional adaptation mechanism.

The proposed current controller consists of an adaptive fuzzy current controller using ANN estimation unit of which the structure diagram is

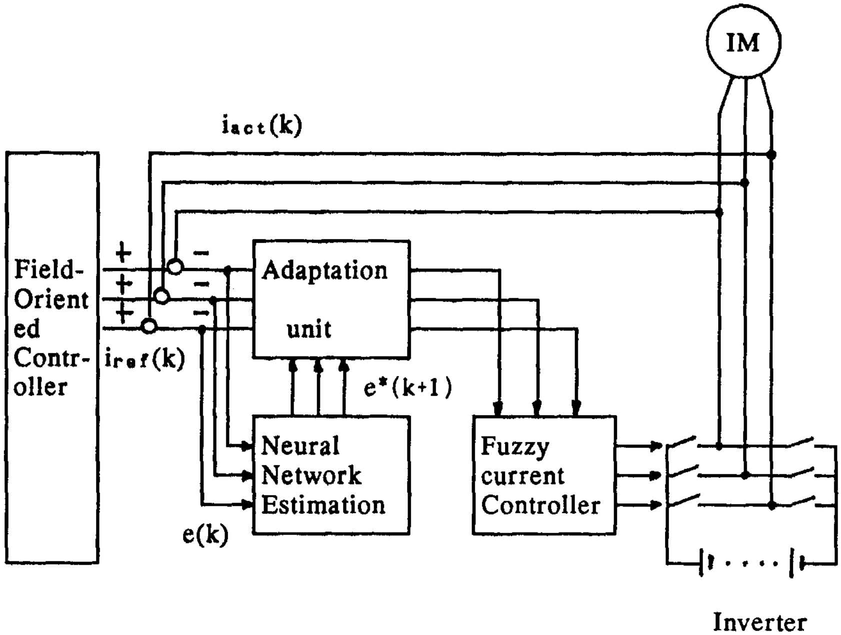



**Figure 1.** Block diagram of proposed current controller.

shown in Figure 1. The fuzzy current controller has two input components: errors modified by ANN estimation outputs and the change of errors of three phase at each sampling time. In order to minimize output current ripple, the fuzzy controller generates PWM pattern signals that will be fed to the inverter drive. The ANN estimation unit learns the characteristic of IM based on current error and train of past error, and it predicts the next error that modifies input of the fuzzy current controller. The proposed controller determines the PWM signals that can adaptively minimize the output current ripple, under unexpected variation of IM parameters and/or controller parameters. The proposed current control architecture improves the performance of the previous fuzzy controller.

## 3. THE FUZZY CURRENT CONTROLLER

This section details the development of the fuzzy current controller for afield-oriented IM drive system. For the convenience of incorporating the intuition and experience of human expert into fuzzy control algorithms, the behavior of the dynamic current response is first investigated. The current error between the reference and actual values of current controller corresponding to one phase $e(k)$, and its error change $\Delta e(k)$ of IM drive system are defined as follows:

$$e(k) = i_{\mathrm{ref}}(k) - i_{\mathrm{act}}(k) \tag{1}$$

$$\Delta e(k) = e(k) - e(k-1) \tag{2}$$

where $i_{\mathrm{ref}}(k)$ represents the reference current of one phase, $i_{\mathrm{act}}(k)$ represents the actual current of one phase in $k$-th sampling interval. The general current response in one arm is shown in Figure 2, where one represents the current response that has multiple switching states affected by switching states in other arms, and the other represents a switching state in one arm.

In accordance with the magnitude and sign of $\Delta e(k)$, actual current is classified into seven cases. For each case, error $e(k)$ is also classified as the same way. The linguistic variables used for identifying each case are defined as follows:

case I: $\Delta e = PB$

case II: $\Delta e = PM$

case III: $\Delta e = PS$

case IV: $\Delta e = ZE$

case V: $\Delta e = NS$

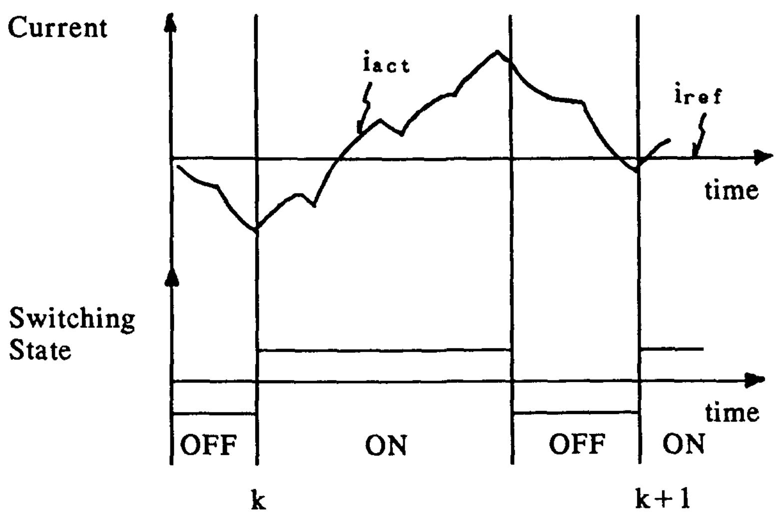



**Figure 2.** Current response corresponding to switching state in one arm.

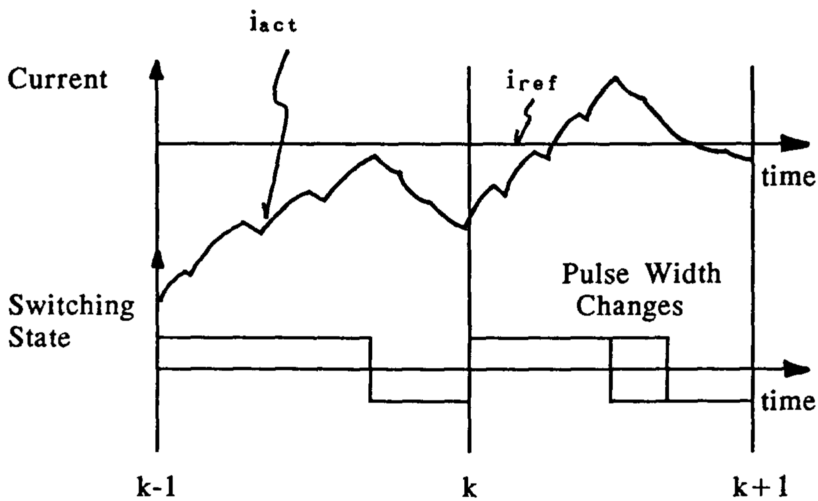
case VI: $\Delta e = NM$

case VII: $\Delta e = NB$

where $N$, $P$, $B$, $M$, $S$, and $ZE$ represent negative, positive, big, small, medium, and zero.

In case I, the magnitude of $e(k)$ is much greater than that of $e(k-1)$. For each case of $e(k)$, the output of fuzzy current controller (the change of the inverter on-time width) should be determined based on expert's intuition and experience in such a way $e(k+1)$ will become zero. For instance, if $e(k)$ is $NS$ and $\Delta e(k)$ is $PB$, then the change of on-time width should be $NM$. $NM$ means that $(k+1)$th on-time width decreases to some extent compared with $k$-th width. This case is illustrated in Figure 3. By applying the same procedure to each case, control output is determined appropriately. The linguistic control rules obtained by above procedure are listed in Table 1.

After determination of fuzzy control rules, the next step is to define the membership functions corresponding to each element in the linguistic set. Even through many types of membership functions have been already developed, for simplicity, triangular membership function are used in this paper. The universe of discourse of the error and error change ranges from $-3[A]$ to $+3[A]$ respectively. The membership functions are shown




where e(k) : NS , Δe(k) = PB

**Figure 3.** Determination of fuzzy control rules.

**Table 1.** Linguistic Control Rules

| Δe e | NB | NM | NS | ZE | PS | PM | PB |
|---|---|---|---|---|---|---|---|
| NB | PB | PB | PB | PM | PM | PS | ZE |
| NM | PB | PB | PM | PM | PS | ZE | NS |
| NS | PB | PM | PM | PS | ZE | NS | NM |
| ZE | PM | PM | PS | ZE | NS | NM | NM |
| PS | PM | PS | ZE | NS | NM | NM | NB |
| PM | PS | ZE | NS | NM | NM | NB | NB |
| PB | ZE | NS | NM | NM | NB | NB | NB |

*Abbreviations:* N, negative; P, positive, B, big; M, medium; S, small; Z, zero.

in Figure 4. Finally for synthesis of the final control action, the center of gravity is used.

The error and error change should be appropriately mapped onto the predefined universe of discourse. The performance of fuzzy control system depends on this scaling mapping. Usually, the procedure for determining the optimal value of these scale factors, however, does not have unique

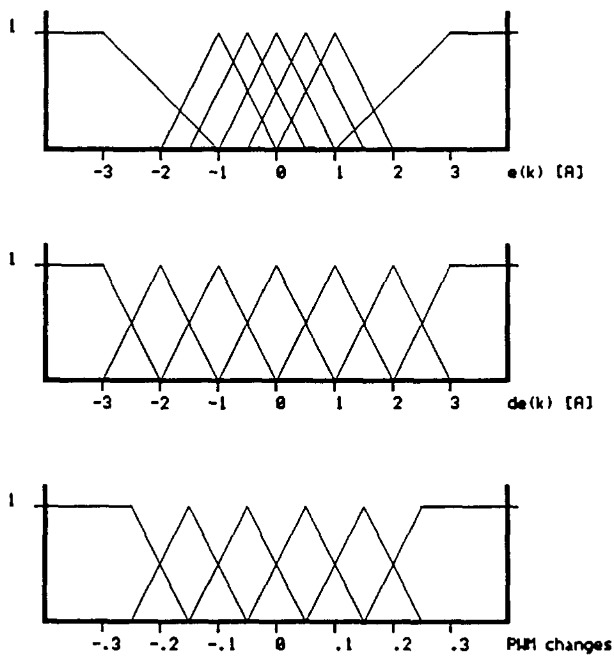



**Figure 4.** Membership functions.

solution. Therefore, optimal performance cannot be guaranteed with arbitrary scale factors. Moreover, parameter variation of IM may incur poor dynamic response with this fixed-scale factors. In this study in order to overcome these drawbacks, the concept of ANN estimation methodology is developed with fuzzy control.

## 4. NEURAL NETWORK ESTIMATION UNIT

ANN has very useful properties. For instance, when the training set contains noisy or inconsistent examples, during the learning phase ANN extracts the characteristics of IM. After learning, ANN can generalize, giving correct responses even in the presence of patterns that are not included in the training set. Furthermore, when the input-output mapping can be obtained by applying some type of rule, the network tends to discover the rule instead of memorizing the input-output pattern pairs. In this paper, we focus our effort on the learning ability of ANN for the enhancement of control performance. Up to date there have been many kinds of learning methodologies of ANN for practical application and new methods are now still under elaboration. This study uses a multilayer perceptron model (PDP-model) with error-back propagation (EBP) that is one of the adaptive learning models, and also one of the most powerful tools in the area of ANN technologies until now [13].

The EBP algorithm uses an objective function, which is defined as the summation of square errors between the desired outputs and the network outputs. It then uses a steepest-descent search algorithm to find the minimum of the objective function. The equations to change the weights of output-layer and hidden-layer, are as follows:

$$\Delta Wpq, k(n+1) = \eta \cdot \delta q, k \cdot \mathrm{OUT}p, j + \alpha \cdot \Delta W_{pq}, k(n) \tag{3}$$

$$Wpq, k(n-1) = Wpq, k(n) + \Delta Wpq, k(n+1) \tag{4}$$

$$\delta q, k = \mathrm{error}q, k \cdot f'(\mathrm{NET}q, k) \tag{5}$$

where,

$\alpha$ = momentum factor

$\eta$ = learning rate

$Wpq, k(n)$ = interconnection weights between $p$'th neuron of output-layer and $q$'th neuron of hidden-layer (subscript $k$ means by the target-layer)

$Wpq, k(n+1)$ = weight values at step (n + 1) error$q$ = the difference between the desired or target value and the actual output at $q$'th neuron of output layer

$\delta q, k$ = back-propagated error at $q$'th neuron of $k$'th-layer.

OUT$p, j$ = output value of neuron $p$ at $j$'th-layer.

NET$q, k$ = NET(summation) value of $q$'th neuron at $k$'th-layer.

$f'(\text{NET}q, k)$ = the differential value of activation function

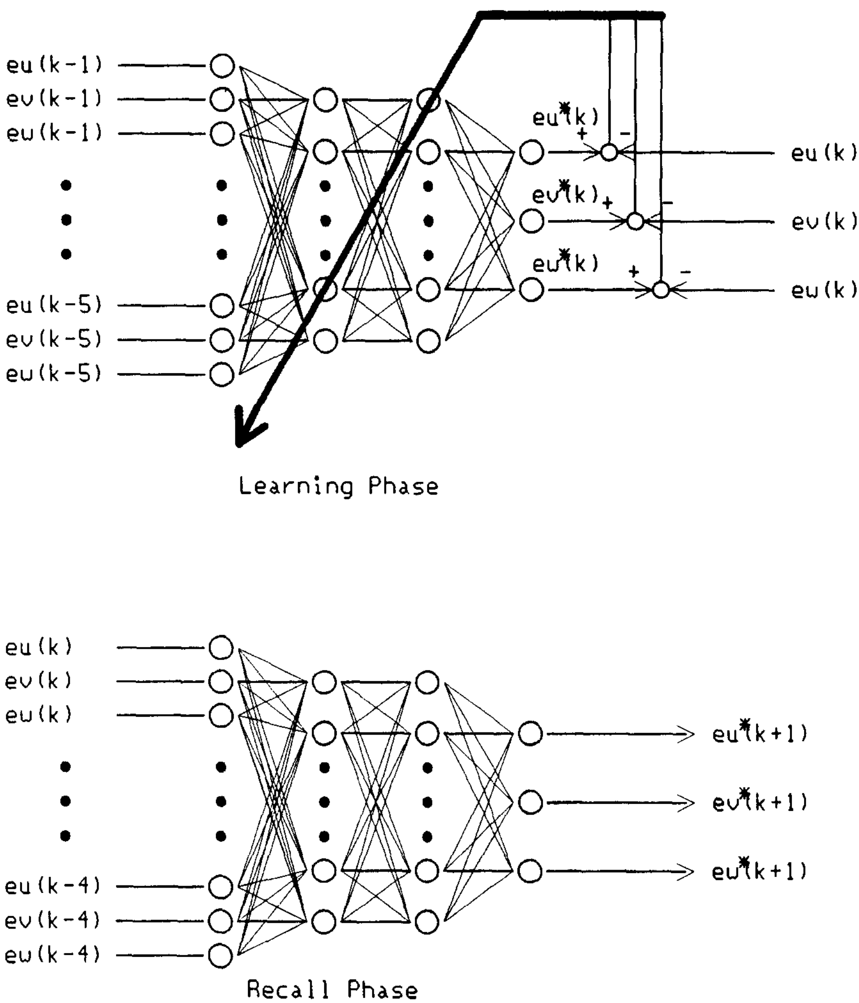



**Figure 5.** The architecture of ANN.

**Table 2.** Parameters for ANN

| Parameters | Values |
|---|---|
| Hidden layer | 2 |
| Neuron of hidden layer 1 | 30 |
| Neuron of hidden layer 2 | 30 |
| Neuron of input layer | 15 |
| Learning rate | 0.5 0.4 0.3 |
| Momentum factor | 0.0 0.0 0.0 |
| Gain of sigmoid function | 0.2 0.2 0.05 |
| Weights initial values | $-0.2 \sim 0.2$ |

Note that above subscripts, "$p$" and "$q$" correspond to a specified neuron in each layer. The symbols "$j$" and "$k$" represent each layer. In the case of hidden-layer, error $\delta q, k$ is obtained by Eq. (6).

$$\delta p, j = \left(\sum \delta q, k \colon Wpq, k\right) f'(\mathrm{NET}p, j) \quad \text{at hidden layer} \tag{6}$$

Figure 5 shows the proposed architecture of ANN, where ANN consists of 15 neurons in the input layer, 30 neurons in two hidden layers respectively, and three neurons in the output layer. Table 2 shows parameters and their values of the developed ANN used for estimation unit.

In the learning phase, the inputs of the ANN for error estimation unit are composed of $e(k-1), \ldots, e(k-5)$ at each sampling time [14]. The outputs of the ANN unit are the estimated present errors, $e^*(k)$ of each phase current. The ANN is learned or trained in such a way that outputs of ANN converge to actual errors. In this study, the differences between the desired or target values and the actual outputs at first, second, and third neuron of output layer are as follows:

$$\text{error } 1 = e_u(k) - e_u^*(k) \tag{7}$$

$$\text{error } 2 = e_v(k) - e_v^*(k) \tag{8}$$

$$\text{error } 3 = e_w(k) - e_w^*(k) \tag{9}$$

When the learning is accomplished with these training samples, the proposed ANN is changed in the recall phase and predicts the next step errors $e^*(k+1)$ of three phases with inputs consisting of $e(k), \ldots, e(k-4)$. This predicted error is used to compensate the input of the fuzzy controller, which determines the PWM on time width.

## 5. SIMULATION RESULTS

In order to test the performance of the proposed control system and compare with other conventional control systems, performance index is defined as follows:

$$I = \sqrt{\frac{\sum\{(i^*u(k) - iu(k))^2 + (i^*v(k) - iv(k))^2 + (i^*w(k) - iw(k))^2\}}{N}} \tag{10}$$

where $i^*u(k)$, $i^*v(k)$, and $i^*w(k)$ represent the reference current of $u$, $v$, and $w$ phase respectively, $iu(k)$, $iv(k)$, and $iw(k)$ represent the actual current, and $N$ represents the sampling number in one period.

For comparison, we used hysteresis band, ramp comparison current control system, which are applied to many commercial industrial drive systems. In addition, the fuzzy controller that has the membership function in Figure 4 and a proposed controller using a completely learned neural network that has same membership function, are also compared. The specification of three-phase 5Hp IM for the simulation is shown in Table 3. In this study the average inverter frequency of each controller is 4 KHz. In general, a hysteresis controller has better characteristics due to the shorter band. It, however, is to obtain a proper switching operation with a shorter band as claimed in [6]. This is because the inverter has some periods of high switching frequency. In this study, the average switching frequency of the hysteresis controller is approximately 4 KHz by setting the hysteresis band to 1[A]. Figure 6 shows the performance index I of each control system with respect to various motor speed $\omega_r$[rad/$s$] at no load operation. As clearly shown in Figure 6, the fuzzy controller has better performance compared with other control systems. Furthermore,

**Table 3.** Specification Data of Three-phase Induction Motor

| | |
|---|---|
| Rating power | 5 Hp |
| Rating voltage | 220 V |
| number of poles | 4 |
| input frequency | 60 Hz |
| $R_s$ | 1.57 Ω |
| $R_r$ | 1.31 Ω |
| $L_s$ | 6.31 mH |
| $L_r$ | 8.19 mH |
| M | 221.3 mH |

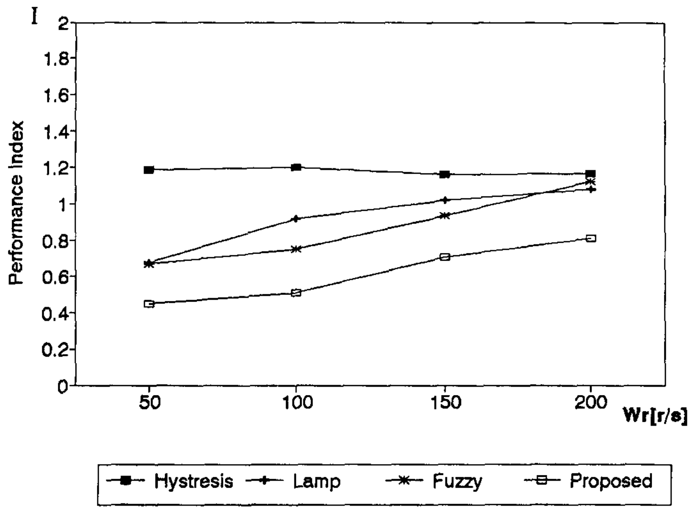



**Figure 6.** Performance of various controllers.

the proposed system, the fuzzy controller with pre-learned for the one-step ahead error prediction, has the best performance compared to others. Even though the hysteresis control system has poor performance compared to other systems, its rms error value remains constant through all operating speed range. As opposed to the hysteresis control system, the rms error value of other control systems tends to increase as operating speed increases. The proposed control system, however, significantly reduces the current ripple through all operating speed ranges.

For detail analysis of control performance on time domain, the current response of each control system (under no load condition with speed reference, 100[rad/s)] is provided in Figures 7–10. Figures 7–10 show the responses of the inverter output current for hysteresis, ramp comparison, fuzzy, and proposed current controller respectively at no load condition. Figure 7 shows the current response of hysteresis controller with hysteresis band 1[A]. As shown in this figure, quite a large current ripple can be observed. Figure 8 shows the current response of ramp comparison controller where the current ripple is significantly reduced compared with the hysteresis controller. But this control system incurs time-delay that deteriorates overall control performance of the field-oriented controller for IM. The current response of the fuzzy control system is shown in Figure 9. Compared to the hysteresis controller and ramp comparison controller, this control system slightly reduces the current ripple as well as time-delay. The current ripple still remains large. The control performance of the proposed control system is illustrated in Figure 10. Compared with Figure

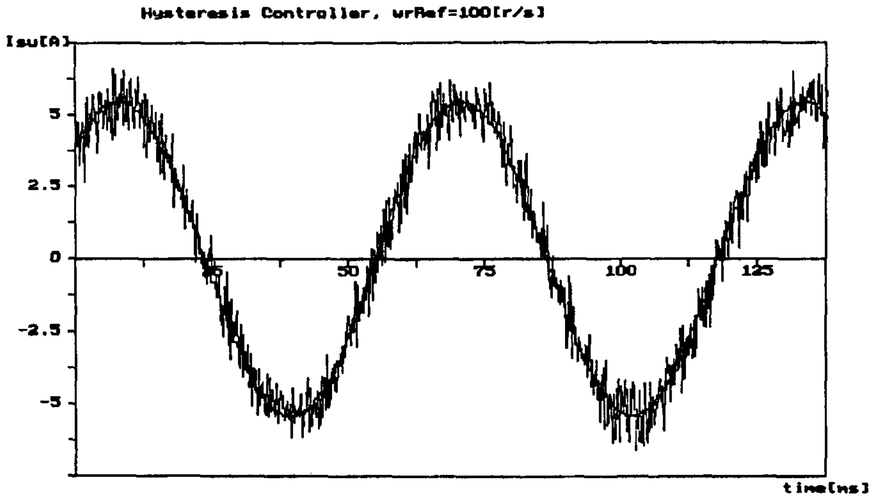



**Figure 7.** Current response of hysteresis controller.

7–Figure 9, the proposed system successfully suppresses current ripple and significantly improves control performance in term of performance index value.

Figure 11 and Figure 12 show the control performance of fuzzy and the proposed control system under variation of rotor resistance. In this simulation, we used a 200% variation of rated rotor resistance. From these

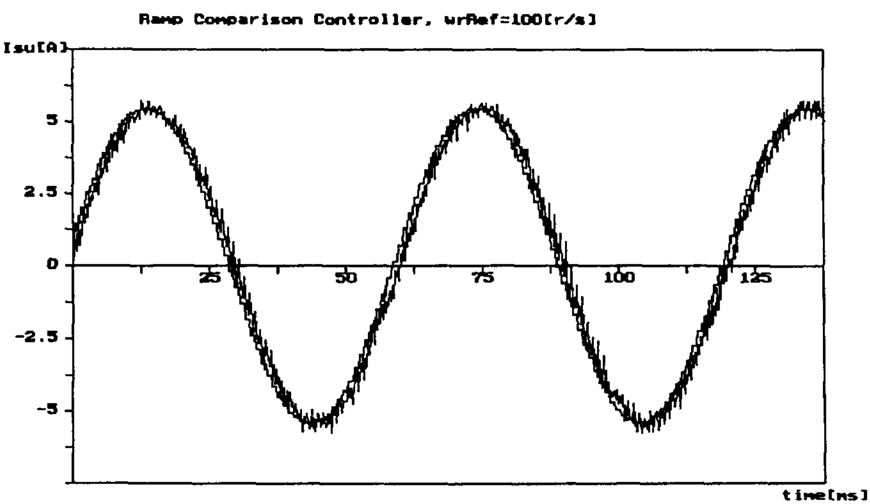



**Figure 8.** Current response of ramp comparison controller.

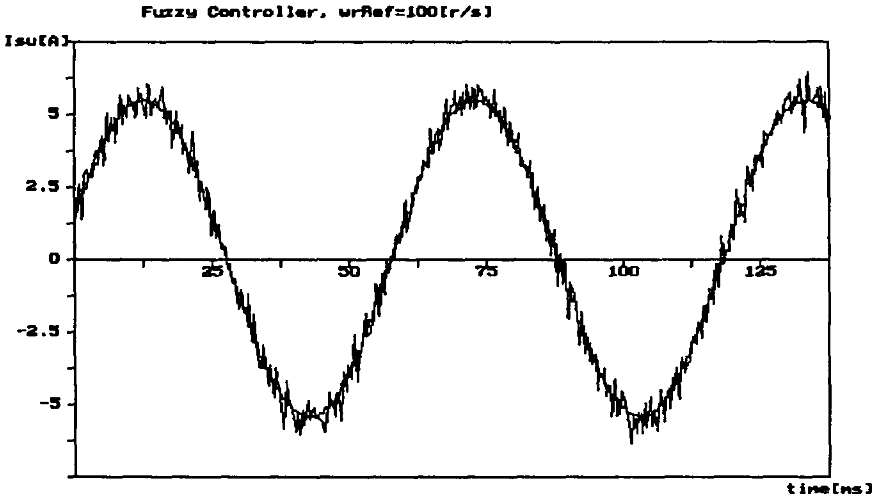



Figure 9. Current response of fuzzy controller.

figures, we can conclude that the control system implemented and based on fuzzy theory is insensitive to the variation of the rotor resistance of IM. Figure 13 shows the current tracking performance of the proposed control system under abrupt load change, As clearly shown, the tracking error is invariant even under abrupt load variation.

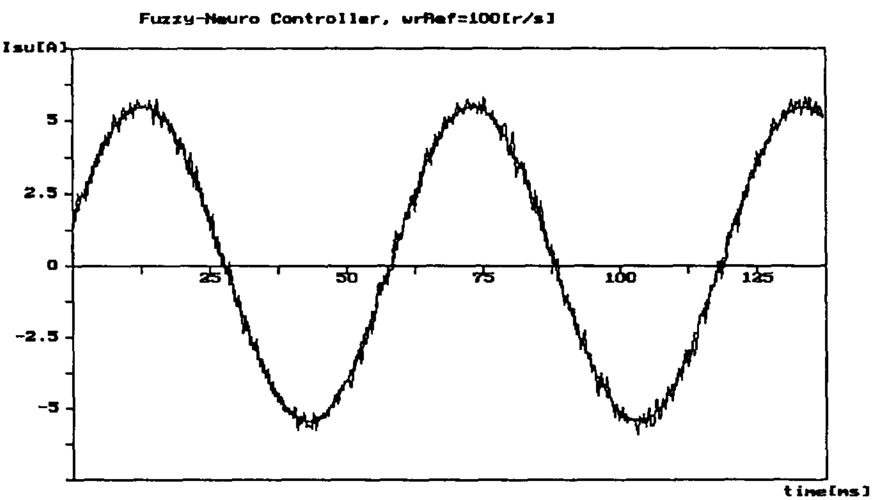



Figure 10. Current response of proposed controller.

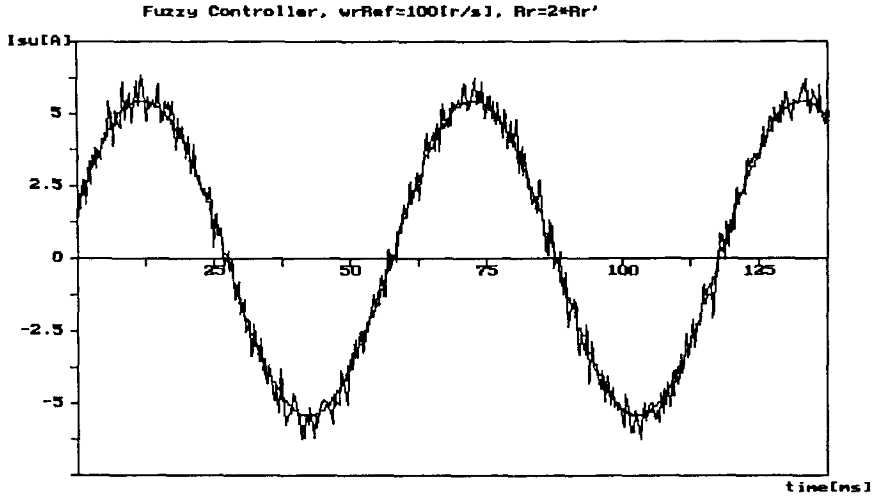



**Figure 11.** Current response of fuzzy controller ($R_r = 2^*R_r^*$).

From the above simulations, we show that fuzzy current controller with neural network has outstandingly better performance through all operating speed ranges. Under the parameter variation and abrupt load changes, the proposed control system has especially good adaptability.

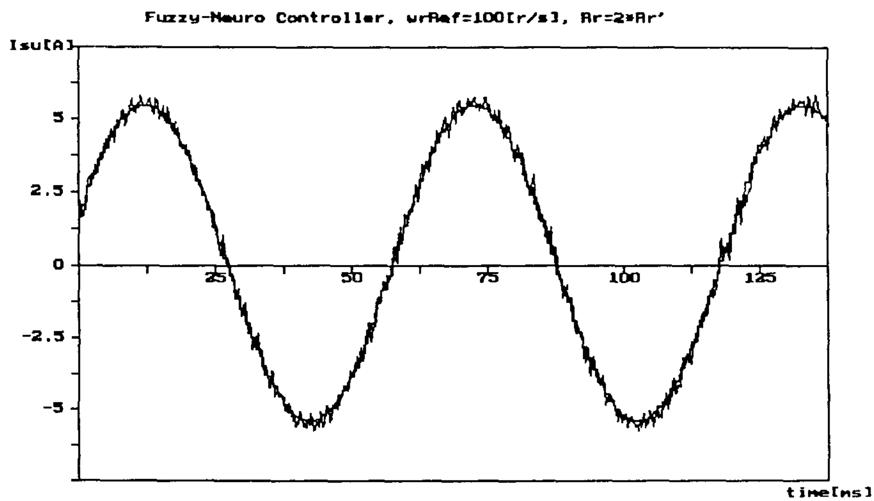



**Figure 12.** Current response of proposed controller ($R_r = 2^*R_r^*$).

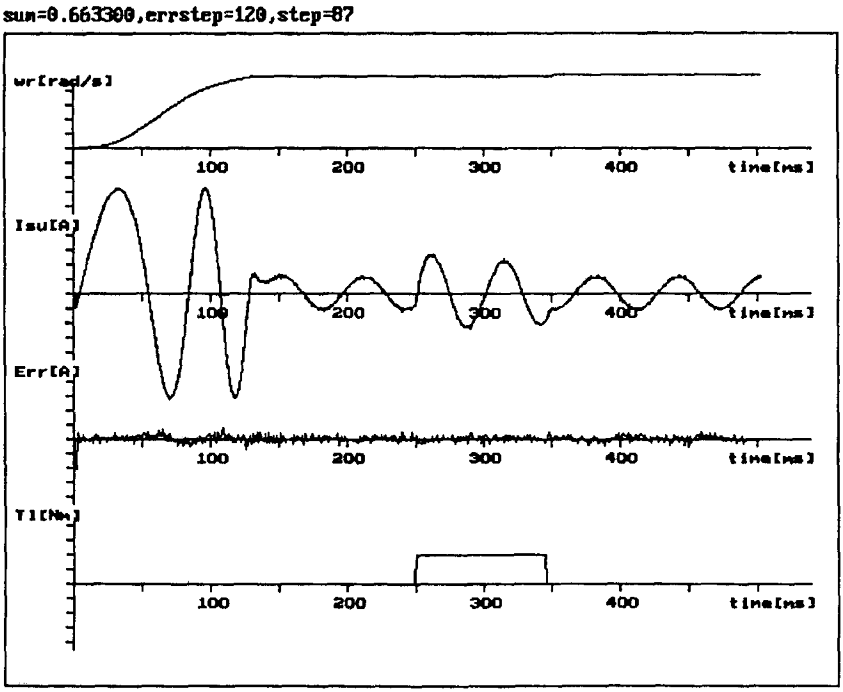



**Figure 13.** Current tracking performance of proposed current controller under abrupt load changes.

## 6. CONCLUSION

In this study, a novel adaptive fuzzy current controller using ANN is proposed. ANN learns the characteristics of IM and modifies the error applied to fuzzy current controller. The proposed control system is applied to the field-oriented controller IM drive system. This study aims at establishing a completely new control system that shows a superb performance compared with conventional IM drive systems even under parameter variations and abrupt load changes. Through the simulations, we verified that the proposed controller has a good adaptability due to ANN learning ability.

For further elaboration related to this research, we will develop a better estimation methodology based on ANN and a better adaptation mechanism in order to reduce the effects of the system parameter variation on control performance.

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